Beyond the Storm: Analysis of the Economic Impacts of Cyclone Bomb Events in the Southern Region of Brazil in 2020.

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Extended Abstract

Special Area: S07 Navigating the Storm: Exploring the Socio-Economic and Behavioural Impacts of Natural Disasters on Communities

In recent years, there has been a significant increase in the frequency and intensity of natural disasters worldwide, which has had profound effects on communities and economies. In Brazil, the southern region of the country is particularly vulnerable to such events due to its location in a corridor that is conducive to the formation of tornadoes and cyclones. The region has experienced a series of catastrophic weather events that have had a profound impact on its socioeconomic fabric.

An example is the Cyclone Bomb that hit the region in 2020. This event is characterized by rapid intensification, commonly known as bombogenesis. The damage and disruption it caused left an indelible mark, claiming at least 12 lives, including nine in Santa Catarina (SC), one in Rio Grande do Sul (RS), and two in Paraná (PR), and affecting more than a million people. The estimated cost of the cyclone's damage is expected to reach billions of Brazilian reais. Figure 1 in Appendix A shows a map of affected cities.

The Cyclone Bomb occurred in late June 2020, causing extensive damage through strong winds, heavy rainfall, and even sporadic snowfall in some areas. Wind speeds reached up to 116 kilometers per hour (approximately 72 miles per hour) in various locations, resulting in power outages, deforestation, structural damage to buildings and transportation disruptions. It had economic impacts beyond the affected areas, affecting businesses, agriculture, infrastructure, and the overall quality of life of the population, demonstrating the region's inherent economic and social integration.

The effects of the Cyclone Bomb were felt in several sectors, especially in agriculture, where crops suffered significant damage, and in the broader economy where commercial entities and infrastructure were disrupted. It should be noted that infrastructure damage in Santa Catarina alone exceeded 20 million euros. Flash floods and mudslides caused by the cyclone resulted in crop losses of up to 30 million euros. In response to the crisis, the Brazilian government implemented financial aid and directed investments towards fortifying infrastructure to mitigate future calamities.

The impacts of extreme weather phenomena have been extensively investigated worldwide. In the global context, Jones et al. (2022) scrutinize the reliability of data concerning human and economic impacts of natural disasters. Additionally, Skidmore (2022) investigated the link between natural disasters and economic growth have been revisited, providing new insights into this complex relationship. Some studies have also empirically reexamined the economic impact of natural disasters as in Panwar and Sen (2019). An important review of models and empirical studies on the economic impacts of natural disasters can be found in Botzen et al. (2019).

In the Brazilian context, an array of studies has intricately examined the interplay between natural disasters and their economic repercussions. In particular, Lima and Barbosa (2018) investigation into the 2008 flash flood in Santa Catarina reveals spatial spillovers, obtaining a 7.6% decrease in GDP per capita in directly affected municipalities during the year of the disaster. Wink Junior et al. (2023) research on the same event focuses on poverty levels, revealing a substantial increase in the likelihood of individuals falling below the extreme poverty line, particularly affecting non-white residents and those in rural areas. de Oliveira (2019) study, centered on Ceará state in Northeast Brazil, highlights the direct damage caused by natural disasters, indicating a reduction in GDP growth rates, particularly in the agriculture and service sectors. Monte et al. (2021) exploration of disaster-related terminology in Brazil emphasizes the evolving nature of such terms and their vital role in effective disaster risk management. Collectively, these studies contribute to a comprehensive understanding of the multifaceted impacts of natural disasters on various aspects of the Brazilian economy.

Given these considerations, it is important to understand how these events affected the economic landscape of southern Brazil. This article aims to analyze the economic impact of one of such economic disasters, namely the Cyclone Bomb on agricultural, industrial, and service production, going beyond the immediate direct effects to uncover the complex chain reaction of impacts and their resulting spatial spillovers on various aspects of society.

It is a challenging task because it requires analyzing events over time and understanding the spatial dynamics of these phenomena. The complexity is further enhanced when considering the interconnections among these climatic events across different geographic domains.

A comprehensive understanding of the effects of natural disasters on the regional economy is crucial to formulating effective mitigation and adaptation policies that promote sustainable development and economic resilience. Improving understanding of the intricate interplay between natural disasters and the regional economy will equip Brazil's southern region to confront imminent climate challenges with greater efficacy.

The methodology used in this paper is based on the studies conducted by Delgado and Florax (2015) and Bardaka et al. (2019). These researchers combine spatial econometrics in DiD models to analyze the direct, indirect (spillover) and total effects namely Spatial Lag X (SLX) models, which include a spatial lag in the independent variables of a treatment of event.

Although the traditional decomposition of direct, indirect, and total effects in spatial models is well established, Delgado and Florax (2015) emphasizes the importance of considering indirect effects when the explanatory variable that is spatially lagged is a binary event. To do so, it is necessary to take into account the proportion of affected neighbors in calculating the average treatment effect on the treated. Assigning weights to indirect effects based on the proportion or probability that affected neighbors are impacted enhances the precision and applicability of the analysis.

The frequently utilized DiD is a popular method in impact evaluation, allowing to evaluate the changes in an outcome due to an intervention by comparing the performance of treated and untreated (control) groups. DiD has extensive utility in empirical studies to estimate causal effects, especially in scenarios where identical preexisting counterfactual and control groups are not feasible. It allows for the control of both unobservable systematic differences between groups and fixed unit effects (Wooldridge (2010); Greene (2017)). The basic premise is that, in the absence of treatment, the (conditional) difference in the trajectories of the outcome variables of interest between the treated and untreated groups remains constant, assuming the existence of (conditional) parallel trends. Furthermore, it is necessary to ensure that the impact of treatment on the treated group has no effect on the results of the untreated group (Angrist et al. (1996); Delgado and Florax (2015)).

When dealing with spatial data, such as at the municipal level, as documented by Anselin and Bera (1998), LeSage and Fischer (2008), and Elhorst (2014), it is highly unlikely that municipal economies do not exert influence on neighboring areas. The channels through which economic outcomes are transmitted between regions are diverse, with trade, the integration of production chains, the mobility of factors of production, transportation, and communication networks as examples, among others.

In this context, spatial econometrics are useful to incorporate the spatial dimension into models, taking into account interdependencies and neighborhood effects between geographic units (Anselin (2003); LeSage and Pace (2009); Elhorst (2017) and Elhorst (2021)). This allows for the decomposition of the impact of exogenous variables into direct, indirect and total effects.

With spatial data the omission of spatial elements in DiD models can lead to bias and inconsistency in the estimated treatment effects. This is because spatial lags can be correlated with the treatment indicator, resulting in a violation of the exogeneity assumption. In the case of DiD for spatial data, the omitted variable is the spatial lag of the treatment indicator.

In addition to this bias, the omission of spatial lags can also lead to the control group not being correctly specified, violating the Stable Unit Treatment Value Assumption (SUTVA). This can happen because observations that are indirectly affected by the treatment may be included in the control group.

The SLX DiD model is an extension of a typical SLX model, inserting spatial lags in the treatment variable ($\delta W \tau_{it}$) allowing for the spatial interaction between treated and untreated individuals according to the following:

$$Y_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 T_t + \alpha_3 \tau_{it} + \phi' X_{it} + \delta W \tau_{it} + u_{it} \tag{1}$$

where D_i is the dummy variable that indicates individual treatment (D=0 individuals not treated, D=1 individual treated); T_t is the dummy variable that indicates period of treatment (T=0 pre-treatment , T=1 post-treatment); τ_{it} is the interaction between D_i and T_t; X_{it} represents the set of covariates used in the estimation to control observable characteristics; $u_{it} \sim N(0, \sigma^2 I)$ and W is the $n \times n$ spatial weight matrix row-standardized.

Equation (1) can be rewritten as:

$$Y_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 T_t + (\alpha_3 I + \delta W)\tau_{it} + \phi' X_{it} + u_{it} \tag{2}$$

Taking the partial derivatives of equation (2) in order to τ_{it} to obtain the treatment impact on the variable Y_{it}:

$$\begin{bmatrix} \frac{\partial Y_1}{\partial \tau_1} & \frac{\partial Y_1}{\partial \tau_2} & \cdots & \frac{\partial Y_1}{\partial \tau_n} \\ \frac{\partial Y_2}{\partial \tau_1} & \frac{\partial Y_2}{\partial \tau_2} & \cdots & \frac{\partial Y_2}{\partial \tau_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial Y_n}{\partial \tau_1} & \frac{\partial Y_n}{\partial \tau_2} & \cdots & \frac{\partial Y_n}{\partial \tau_n} \end{bmatrix} = (\alpha_3 I + \delta W) \tag{3}$$

The average of the elements of the main diagonal constitutes the direct effect given by (α_3). In general, for spatial econometric models, the elements outside the main diagonal represent the individual indirect effects, the spillovers. Summed individual indirect effects and divided by n (the matrix size), they result in the average indirect effect LeSage and Pace (2009).

However, in the spatial DiD model Delgado and Florax (2015) demonstrate that *with spatially interactive responses the average effect of treatment become a function of the magnitude of the direct effect of treatment, the strength of the local spatial interaction, and the proportion of treated neighbors.* The indirect effects are defined through a linear dose-response type function, in which the municipality is affected according to the share of its neighbors that are affected (Bardaka et al. (2019)).

This study uses publicly available data to examine the economic impact of Cyclone Bomb events in Brazil. The outcomes of interest measure the value added and employment in the agricultural, industrial, commercial and services sectors. These variables, along with population information, are obtained from the annual reports on the website of the Brazilian Institute of Geography and Statistics (IBGE).

Data on the municipalities affected by the Cyclone Bomb can be obtained from the Ministry of Integration and Regional Development. Control variables related to voting behavior and political orientation are extracted from the Brazilian Electoral Justice. These covariates focus on electoral participation and political party alignment between local and state governments and serves as a proxy for local institutional quality, reflecting civic engagement and recent literature suggesting its impact on local growth (Barone and Mocetti (2014); Lima and Barbosa (2018);Asher and Novosad (2017); Niquito et al. (2021)).

The panel data covers the years 2019 and 2021 for all municipalities in the southern region of Brazil.

All models were estimated using Spatial Two-Way Fixed Effects (S2WFE) as described by Delgado and Florax (2015) and Bardaka et al. (2019).

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1 Appendix

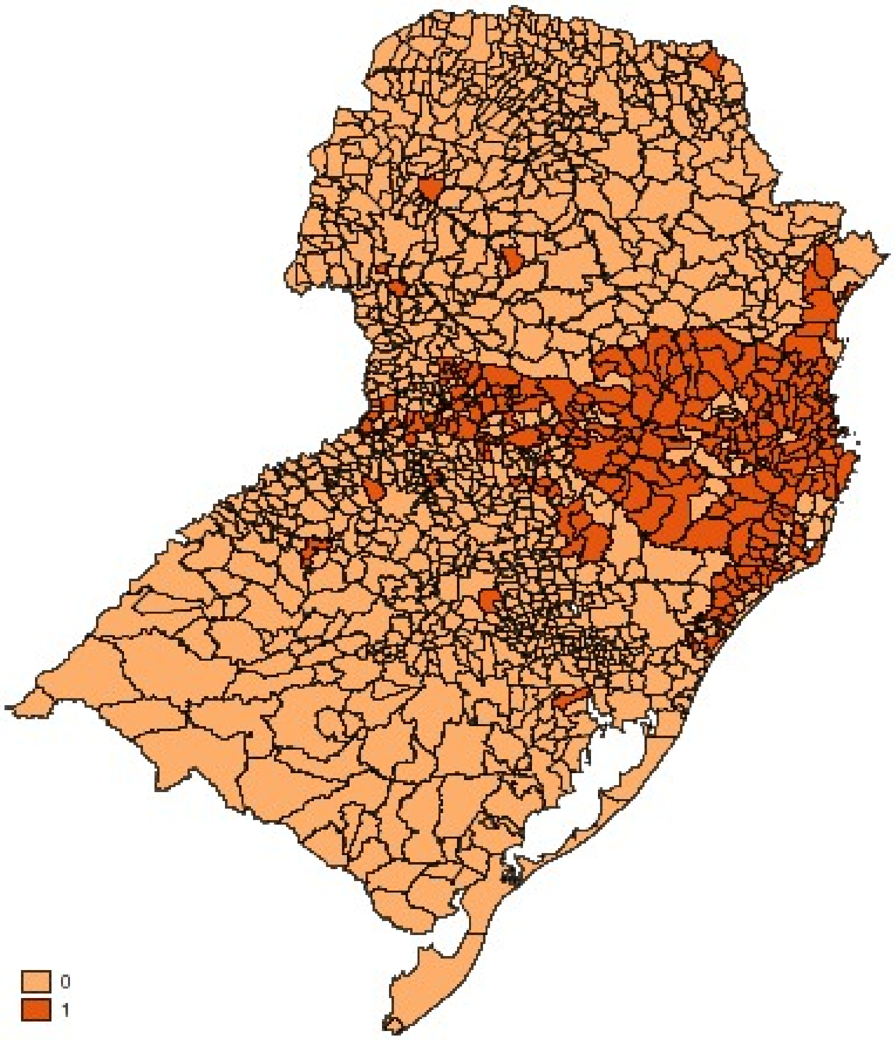

Figure 1: Municipalities affected by the Cyclone Bomb of 2020 (=1 if affected; =0 otherwise)